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ABSTRACT

The nature and appropriate application of the technique of multivariate analysis are discussed. More specifically, the intent of the paper is to demystify and explain the use of multivariate analysis as well as provide guidelines for selection of the most effective statistics for use in specific situations. For the purpose of this paper, the term multivariate indicates that there is more than one dependent variable that one is interested in analyzing simultaneously. The term univariate is used to mean any technique in which there is one dependent variable that is being analyzed. The relationship between multivariate analyses and canonical analysis is discussed, with specific reference to canonical correlation, multiple discriminant analysis, multivariate analysis of variance, multivariate analysis of covariance, and chi square analysis. It is demonstrated that multivariate techniques are subsets of canonical analysis and multiple regression analysis. The discussion of multiple regression analysis covers analysis of variance, analysis of covariance, discriminant analysis, chi square statistics, and t-tests. It is concluded that what frequently appears to be a multivariate analysis question may in fact be a univariate analysis question when one focuses on determining why the research is being conducted and how the results are likely to be used. It is this focus that should lead to the selection of a statistical model or technique. It is argued that considerations of the researcher's intent and the use to be made of the results are much more important than concerns about the Type I error rate. Moreover, univariate analyses are easier to interpret than multivariate analyses and, therefore, less prone to misinterpretation. (TJH)

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THERE IS NO SUCH THING AS MULTIVARIATE ANALYSIS: ALL ANALYSES ARE UNIVARIATE! (Presidential Address)

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There Is No Such Thing As Multivariate Analysis: All Analyses Are Univariate!

(Presidential Address)

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Presented at Midwestern Education Research Association, Chicago, Illinois, October, 1988

Introduction

A large number of works such as Cliff and Krus (1982), Hayes (1973), Edwards (1972), Cooley and Lohnes (1971), Finn (1974), Kendall (1975), and Tatsuoka (1971) has been written to explain when one statistical technique should be used instead of another. Selection of the appropriate technique is frequently based on underlying assumptions, Type I error rates, Type II error rates, etc., with the focus too often being placed on the statistics rather than on how well the statistical technique (model) reflects the specific question of interest. It seems that, for the researcher, the most important concern should be how well the selected statistical procedure is capable of being interpreted correctly as it relates to the question of interest.

Similarly, one has to keep in mind that statistical models were originally designed to simplify, rather than make more complex, the interpretation of data. This can best be accomplished by selecting the simplest models appropriate for the research question. However, a certain amount of prestige has become associated with people who use the most complicated and sophisticated statistical techniques. Editors of journals, colleagues, and students seem to reinforce this tendency to overuse the most sophisticated statistics. As Nie et al. (1975), the authors of the Statistical Package for the Social Sciences (SPSSX), cautioned, the ease of access often means overaccess.

One of the major purposes of writing this paper is to help demystify multivariate* analysis. It is believed that many of the individuals who use multivariate analysis use it for reasons that are not logically justifiable. Some of the reasons most frequently given for using a multivariate approach are:

1. When a researcher has multiple dependent variables and wants to control for a Type I error rate. (This is the most frequent reason given.)
2. Multivariate techniques tend to be more prestigious.
3. They are more likely to get the research published.
4. They will increase statistical power.

Of the reasons given, not one suggests that the multivariate technique better fits the question of interest.

The second intent of this paper is to explain that multivariate analyses are conceptually univariate analyses. An understanding of this concept will make the teaching of multivariate statistics clearer and will improve students' understanding of the relationships between univariate and multivariate techniques, so that they will be less likely to misuse them.

The two stated purposes, to demystify and explain the use of multivariate analysis, are not independent of each other. They are also related to a third concern, which is the selection of the most effective statistics to use in specific situations.

Multivariate Analyses as Subsets of Canonical Analysis

Defining Canonical Correlation: One of the initial publications of multivariate analysis was the publication by Hotelling (1935) of canonical correlational procedures. Canonical correlation has been called the parent technique of multivariate statistics. Kelly, Beggs, McNeil, Eichelberger, and Lyon (1969), Tatsuoka (1971), Cachigan (1982), and others have explicated how multivariate analysis of variance, multivariate analysis of covariance, and multiple discriminant analysis can all be shown to be mathematically derived from canonical correlations (Tatsuoka, 1988).

Canonical correlation is defined as the relationship between two sets of weighted linear components. Generally one of the two sets is considered a predictor set (Xs) and the other is generally considered the criterion set (Ys). The predictor and criterion sets are usually expected to be continuous. However, in reality they can be continuous or categorical. Example 1 is a conceptual presentation of the linear components of a canonical analysis problem when all the variables are continuous.

*The definition of multivariate vs. univariate has not been consistent. For the purpose of this paper, when the term multivariate is used, it is meant that there is more than one dependent variable that one is interested in analyzing simultaneously. Univariate, on the other hand, is using any technique in which there is one dependent that is being analyzed.

I would like to thank Dr. Kenneth Hoedt for his help in reading this paper and for his valuable input.

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$$b_1Y_1 + b_2Y_2 + b_3Y_3 = a_1X_1 + a_2X_2 + a_3X_3$$

$$b_1\begin{bmatrix}3\\5\\7\\8\end{bmatrix} + b_2\begin{bmatrix}7\\12\\9\\3\end{bmatrix} + b_3\begin{bmatrix}15\\18\\22\\27\end{bmatrix} = a_1\begin{bmatrix}1\\2\\3\\4\end{bmatrix} + a_2\begin{bmatrix}5\\9\\7\\15\end{bmatrix} + a_3\begin{bmatrix}18\\3\\9\\7\end{bmatrix}$$

Example 1

Multiple Discriminant Analysis. In the case where the predictor set is continuous and the criterion set is categorical, the type of canonical correlation analysis made is known as multiple discriminant analysis (Example 2).

$$b_1Y_1 + b_2Y_2 + b_3Y_3 = a_1X_1 + a_2X_2 + a_3X_3$$

$$b_1\begin{bmatrix}1\\1\\0\\0\\0\\0\end{bmatrix}_{\text{GROUP 1}} + b_2\begin{bmatrix}0\\0\\1\\1\\0\\0\end{bmatrix}_{\text{GROUP 2}} + b_3\begin{bmatrix}0\\0\\0\\0\\1\\1\end{bmatrix}_{\text{GROUP 3}} = a_1\begin{bmatrix}1\\2\\3\\4\\8\\7\end{bmatrix} + a_2\begin{bmatrix}5\\9\\7\\15\\18\\9\end{bmatrix} + a_3\begin{bmatrix}18\\3\\9\\7\\6\\4\end{bmatrix}$$

Example 2

Multivariate Analysis of Variance. When the predictor set is made up of categorical variables and the criterion set is continuous, the canonical correlational analysis is frequently called multivariate analysis of variance.

$$b_1Y_1 + b_2Y_2 + b_3Y_3 = a_1X_1 + a_2X_2 + a_3X_3$$

$$b_1\begin{bmatrix}3\\5\\7\\8\\2\\9\end{bmatrix} + b_2\begin{bmatrix}7\\12\\9\\3\\4\\7\end{bmatrix} + b_3\begin{bmatrix}15\\14\\22\\27\\28\\29\end{bmatrix} = a_1\begin{bmatrix}1\\1\\0\\0\\0\\0\end{bmatrix}_{\text{TR.}_1} + a_2\begin{bmatrix}0\\0\\1\\1\\0\\0\end{bmatrix}_{\text{TR.}_2} + a_3\begin{bmatrix}0\\0\\0\\0\\1\\1\end{bmatrix}_{\text{TR.}_3}$$

Example 3

Multivariate Analysis of Covariance. Example 4 is a situation in which the predictor set is made up of both categorical and continuous variables; the criterion variables are continuous and the researcher wants to hold the continuous predictor variables constant. This example has been traditionally known as multivariate analysis of covariance.

$$b_1Y_1 + b_2Y_2 + b_3Y_3 = a_1X_1 + a_2X_2 + a_3X_3$$

$$b_1\begin{bmatrix}3\\5\\7\\8\\2\\9\end{bmatrix} + b_2\begin{bmatrix}7\\12\\9\\3\\4\\7\end{bmatrix} + b_3\begin{bmatrix}15\\14\\22\\27\\28\\29\end{bmatrix} = a_1\begin{bmatrix}1\\1\\1\\0\\0\\0\end{bmatrix}_{\text{TR.}_1} + a_2\begin{bmatrix}0\\0\\0\\1\\0\\0\end{bmatrix}_{\text{TR.}_2} + a_3\begin{bmatrix}18\\3\\9\\7\\5\\9\end{bmatrix}_{\text{COV.}}$$

Example 4

KxK Chi Square. If in the canonical correlational analysis both the predictor and criterion sets are categorical, the analysis results in a chi square (Leitner, 1979) (Example 5).

$$b_1Y_1 + b_2Y_2 + b_3Y_3 = a_1X_1 + a_2X_2 + a_3X_3$$

$$b_1\begin{bmatrix}1\\1\\0\\0\\0\\0\end{bmatrix} + b_2\begin{bmatrix}0\\0\\1\\1\\0\\0\end{bmatrix} + b_3\begin{bmatrix}0\\0\\0\\0\\1\\1\end{bmatrix} = a_1\begin{bmatrix}1\\0\\1\\0\\1\\0\end{bmatrix} + a_2\begin{bmatrix}0\\0\\0\\1\\1\\1\end{bmatrix} + a_3\begin{bmatrix}1\\1\\0\\0\\1\\1\end{bmatrix}$$

Example 5

The brief definitions and examples presented above demonstrate how the presented multivariate techniques are conceptually subsets of canonical analysis. A further examination of canonical correlation procedures is presented below. The canonical Rc is really a Pearson product moment correlation (r) between the two linear composite sets (Z and W) which produce the canonical correlation. The composition of Z and W are as follows:

$Z = a_1X_1 + a_2X_2 + a_3X_3$

Where: a_1-a_3 = raw canonical coefficients

X_1-X_3 = the factor components of the predictor set that account for 100% of the trace of the predictor set.

$W = b_1Y_1 + b_2Y_2 + b_3Y_3$

Where b_1- b_3 = raw canonical coefficients

Y_1-Y_3 = the factor components of the criterion set (that account for 100% of the trace of the criterion set.

After the sets of Z and W are composed, the canonical R (Rc) is the Pearson correlation between W and Z.

An additional relationship between canonical correlation and a multivariate technique is apparent when you consider that a multiple regression equation is really nothing more than a canonical correlation in which you have continuous predictor variables and only one continuous criterion variable. (Note, as with canonical analysis, the predictor variables can be categorical, continuous, or both, and the criterion variables can be continuous or categorical [Example 6]).

$$Y = a_1X_1 + a_2X_2 + a_3X_3$$

$$\begin{bmatrix}3\\5\\7\\8\end{bmatrix} = a_1\begin{bmatrix}1\\2\\3\\4\end{bmatrix} + a_2\begin{bmatrix}5\\9\\7\\15\end{bmatrix} + a_3\begin{bmatrix}18\\3\\9\\7\end{bmatrix}$$

Example 6

Univariate Techniques as Subsets of Multiple Regression Analyses.

Analogous to how "multivariate analyses" are subsets of canonical analyses, univariate analyses are subsets of multiple linear regression.

Analysis of Variance. In an MLR equation, when the predictor variables are categorical and the criterion variable is continuous the regression analysis is frequently called analysis of variance (Example 7).

$$Y = a_1X_1 + a_2X_2 + a_3X_3$$

$$Y_1 = Tr._1 + Tr._2 + Tr._3$$

$$\begin{bmatrix}3\\5\\7\\8\\9\\10\end{bmatrix} = a_1\begin{bmatrix}1\\1\\0\\0\\0\\0\end{bmatrix} + a_2\begin{bmatrix}0\\0\\1\\1\\0\\0\end{bmatrix} + a_3\begin{bmatrix}0\\0\\0\\0\\1\\1\end{bmatrix}$$

example 7

Analysis of Covariance. When an MLR equation has a predictor set of variables, one or more of which is being held constant, while predicting a continuous criterion variable , the analysis is frequently called analysis of covariance (Example 8).

$$Y = Tr._1 + Tr._2 + Cov.$$

$$\begin{bmatrix}3\\5\\7\\8\end{bmatrix} = a_1\begin{bmatrix}1\\1\\0\\0\end{bmatrix} + a_2\begin{bmatrix}0\\0\\1\\1\end{bmatrix} + a_3\begin{bmatrix}18\\3\\9\\7\end{bmatrix}$$

Example 8

Discriminant Analysis. Multiple linear regression analyses in which the set of predictor variables is continuous and the criterion set is dichotomous are frequently called a discriminant analysis (Example 9).

$$Y = a_1X_1 + a_2X_2 + a_3X_3$$

$$\begin{bmatrix}1\\1\\0\\0\end{bmatrix} = a_1\begin{bmatrix}1\\2\\3\\4\end{bmatrix} + a_2\begin{bmatrix}5\\9\\7\\15\end{bmatrix} + a_3\begin{bmatrix}18\\3\\9\\7\end{bmatrix}$$

example 9

Hotelling's T^2, which is multivariate t-test, is suggested for situations in which there are two groups being simultaneously compared on a number of dependent variables, while controlling for the correlation between the dependent variables. The following regression equation will give the same results as the Hotelling's T^2:

$$Y = a_0U + a_1D_1 + a_2D_2 + a_3D_3$$

$$\begin{bmatrix}1\\1\\1\\1\\0\\0\\0\\0\end{bmatrix} = a_0\begin{bmatrix}1\\1\\1\\1\\1\\1\\1\\1\end{bmatrix} + a_1\begin{bmatrix}3\\5\\7\\8\\2\\1\\6\\3\end{bmatrix} + a_2\begin{bmatrix}9\\8\\7\\6\\8\\9\\8\\2\end{bmatrix} + a_3\begin{bmatrix}5\\5\\4\\4\\2\\3\\1\\1\end{bmatrix}$$

Where Y = 1 if from Group 1, 0 otherwise. D_1 through D_3 are the dependent variables used in the Hotelling T^2. $a_0 \ldots a_3$ are partial regression weights that will take into consideration the correlation between the D's (the dependent variables in the Hotelling's T^2).

Chi Square. Example 10 demonstrates a problem in which the criterion variable is dichotomous and the predictor variables are categorical; this type of analysis is frequently called chi square. By doing appropriate data transformations, such as logit transformations, one can do a logit analysis, which is a subset of a log-linear analysis.

$$Y = a_1X_1 + a_2X_2 + a_3X_3$$

Dem/Rep = Black + White + Other

$$\begin{bmatrix}1\\1\\1\\0\\0\\0\end{bmatrix} = a_1\begin{bmatrix}1\\0\\1\\0\\1\\0\end{bmatrix} + a_2\begin{bmatrix}1\\1\\0\\0\\1\\1\end{bmatrix} + a_3\begin{bmatrix}1\\1\\0\\1\\0\\1\end{bmatrix}$$

Example 10

t-tests. When, in a multiple linear regression analysis, the predictor set is made up of two variables identifying memberships in one of two groups, and the criterion variable is continuous, what is equivalent to a t-test has been used to analyze the data (Example 11).

$$Y_1 = a_1X_1 + a_2X_2$$

$$Y = Tr._1 + Tr._2$$

$$\begin{bmatrix} 3 \\ 5 \\ 7 \\ 8 \end{bmatrix} = a_1 \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} + a_2 \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}$$

Example 11

By putting the appropriate person vectors into the multiple linear regression equations, analyses of repeated measures designs and trend analyses can be made. (Obviously, the above definitions of the univariate analyses assume that one will test the appropriate full models against the appropriate restricted models. See McNeil, Kelley, McNeil, 1972; Cohen & Cohen, 1975; Pedhazur & Kerlinger, 1982. The explanation of these models goes beyond the scope and purpose of this paper.)

Consider the regression model $Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3$, where $a_1 - a_3$ = partial regression weights, $X_1 - X_3$ = predictor variables, a_0 is the intercept, and Y = observed scores for the criterion. It follows that a multiple R is nothing more than the Pearson correlation (r) between the predicted $\hat{Y}$ (that is,Y) and the observed Y. (This concept was similarly explicated in the discussion of canonical Rc where the canonical Rc between subsets Z and W was indicated to be a Pearson product correlation coefficient.)

General Discussion

The above presentation showing how the canonical Rc and the multiple R are really nothing more than weighting variables and then running sample r's was presented to give credence to the following statement. All multivariate analyses can be explained by subsets of univariate analyses. The initial statement was that virtually all analyses can be thought of as a subset of canonical. It is equally true that all analyses can be thought of as putting little r's together. For pedagogical purposes and understanding, I believe students will better grasp what a "multivariate analysis" represents, and will be less likely to be mystified by what is happening in the "multivariate black box," if they are aware that a multivariate analysis is nothing more than a set of little r's.*

*A factor analysis and a component analysis are conceptually no more than looking at a correlation matrix and grouping the items that are most highly intercorrelated together. Also, a factor loading is conceptually a correlation between an item and a factor.

As was stated at the beginning of this presentation, the most frequent reason given for using "multivariate" statistics is to control for the Type I error rate when using multiple dependent variables. It is true that "multivariate analysis" will control for the Type I error rate for the overall multivariate test. However, where interpretation of results moves to determining where the significance lies for each criterion variate, a correction for multiple testing has to be incorporated to control for Type I error. This is necessary because the multiple testing that is needed to identify where significances lie will produce an alpha error buildup. This rationale is analogous to doing a one-way analysis of variance on five groups and finding that there is an overall statistical significance (all the treatments are not equal). The overall F-test does control for the Type I error. However, to determine where the difference exists, testing treatment 1 against 2, 1 against 3, etc., will produce alpha error buildup and a usual post-hoc analysis to control for alpha error build-up is necessary.

Most frequently, proponents for "multivariate analysis" tend to forget that the overall multivariate test for significance is the only aspect of the multivariate testing sets of procedures that does not need to be corrected for Type I error. Anytime in the multivariate situation where one does additional tests to determine where the significance lies, a control for multiple comparisons is necessary to keep the Type I error rate constant (Croom & Newman, 1988; Newman, Croom, Mugrage & Hoedt, 1983; Croom, 1986).

There is nothing about "multivariate analysis" that gives it immunity to its multiple testing procedures, as it effects alpha error build-up. Both "multivariate" and univariate procedures require adjustment to control for alpha error build-up when additional tests of significance are done.

As stated earlier, one of the more important considerations in determining whether one should use "multivariate" or univariate procedures, should be how well the statistical procedure reflects the question of interest. In an article by Newman and Benz (1986) which compared canonical correlation to univariate factor regression, the argument was made that many questions which seem to be of multivariate canonical concerns may really be better reflected by univariate factor regression. The following are abstracted examples from their paper that demonstrate such questions, concerns that might better be reflected by univariate factor regression.

1. What is the relationship between the predictor set (attitude, self-concept, locus of control, overweight, and hours of T.V. watched) and the criterion set (reading, math, and science)?

2a. What is the relationship between the predictor set

(attitude, self-concept, locus of control, overweight, and hours of T.V. watched) and reading achievement independent of math and science achievement?

2b. What is the relationship between the predictor set and science achievement independent of reading and math achievement?

2c. What is the relationship between the predictor set and math achievement independent of science and reading achievement?

2d. What is the total variance in reading achievement accounted for by the predictor set of variables?

2e. What is the common variance in reading, math, and science achievement that can be accounted for by the predictor set?

Given the same set of variables, one can ask also:

3. What is the relationship between the underlying constructs of the predictor set and the underlying constructs of the dependent set?

Question 3 is one most traditionally viewed as appropriate for canonical correlation analysis. The question is: "What is the relationship between the underlying constructs of the predictor set and the underlying constructs of the dependent set?" Obviously, this is what canonical correlation estimates. In investigating this question, an alternative to the canonical approach might be the following. One could factor analyze both sets simultaneously to determine which items rotate on which factors. If there are certain predictor variables that load on the same factor as certain criterion variables, this would indicate that those particular predictor variables and those particular criterion variables are measuring the same underlying construct.

Another approach is to factor analyze both sets using an eigenvalue of zero as a cutoff, therefore accounting for 100% of the variance in both sets. Then one would use predictor sets of factors predicting each of the criterion factors. (The Newman and Benz paper presented the actual models needed to test the above questions as presented. However, since explication of these models goes beyond the scope of this paper, they are not presented here.) Newman and Benz (1986) presented the argument that the univariate analysis is easier to interpret and is likely to reflect the question of interest. Croom (1986), in a Monte Carlo study, also presented evidence that the sets of univariate analysis that were written to reflect a "multivariate question" were as accurately interpreted as the "multivariate analysis" in their reflection of the data.

Conclusion

As indicated by Newman and Benz, what frequently appears to be a "multivariate analysis" question may turn out to be a univariate question when one focuses on determining why the research was conducted and how the results are likely to be used. It is this focus that should lead to the selection of a statistical model or technique. I believe that consideration of the researcher's intent and the use to be made of results are much more important than concerns regarding the Type I error rate, especially since one can control for Type I error build-up due to multiple dependent variables in univariate situations as demonstrated by Croom (1986) and Croom and Newman (1988). In terms of power, one may find significance due to underlying constructs. If this significance is found, it must be kept in mind that these constructs are very unstable, especially when not hypothesized. Therefore, extreme care must be used in interpreting the results. On the other hand, if one thought there was an underlying construct of interest, then the researcher could factor analyze the variables of interest and rotate them to increase interpretability and then cross-validate them to estimate stability. Factor regression, as suggested by Newman and Benz (1986) could then be used. This procedure of factor regression will have no less power than the traditional multivariate procedure and will more likely increase interpretability. Realizing that there is nothing really unique about "multivariate analysis" and that it is really sets of univariate analyses, one is more likely to think about which models best fit the question and be less concerned with the secondary issue of alpha error build-up, which can be handled by using appropriate and easily available corrections.

Since most consumers of research agree that univariate analyses are easier to interpret than multivariate analyses and are therefore less prone to misinterpretation, and since studies like Croom and Newman (1988) and Croom (1986) demonstrate that one can write sets of univariate models to reflect the "multivariate questions" as accurately as the multivariate analysis, shouldn't the univariate analysis approach be used?

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Potential readings of interest:

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(Membership Survey continued from page 1)

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Sonya Blixt and Tom Dinero